Price Discovery between Bitcoin Spot Markets and Exchange Traded Products ⋆

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Abstract

We examine price discovery dynamics between Bitcoin exchange-traded products (ETPs) and spot markets on centralised cryptocurrency exchanges. We apply four popular price discovery measures to ETP and spot transaction data between August 2021 and July 2022. Our results show that price discovery is dominated by the spot market across all measures and sampling frequencies. This implies that ETP markets play a smaller role in the incorporation of new information about Bitcoin prices, and that informed investors largely prefer to trade on spot markets that offer significantly deeper liquidity and operate round the clock.

Keywords: cryptocurrency, Bitcoin, price discovery, market efficiency, exchange-traded products

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1. Introduction

The process through which new information is efficiently incorporated into asset prices is less clear when trading in an asset is fragmented across multiple venues or markets. In such a scenario, it is of interest to identify where price discovery takes place (Hasbrouck, 1995).

Crypto spot exchanges have attracted significant interest from both retail and institutional investors. As regulations constrained the ability of traditional funds and banks to participate in these exchanges, an opportunity arose to create a more traditional product allowing exposure to Bitcoin and other cryptocurrencies. Thus, Bitcoin Exchange-Traded Products (ETPs) allow investors on traditional equity exchanges to gain exposure to the underlying asset without the need to hold Bitcoin.

Evidence suggests that these products have witnessed significant fund flows, with over 180 active crypto ETFs, ETPs, and trusts in existence. Approximately half of these have been launched since late 2021, during which time the total value of underlying crypto assets dropped by 70%, from $84 billion to $24 billion[1]. With traditional investors and institutions now able to access crypto markets, we aim to examine the extent to which the ETP market offers a venue for Bitcoin price discovery.

Previous literature has mainly focused on the lead-lag relationship between futures and spot markets, with the overarching hypothesis that price discovery predominantly occurs in futures markets. Studies have presented evidence in support of this across markets including equities (Kawaller et al., 1987; Chan, 1992; Wahab and Lashgari, 1993; Koutmos and Tucker, 1996; Booth et al., 1999; Tse, 1999; Hasbrouck, 2003; Covrig et al., 2004; So and Tse, 2004; Bohl et al., 2011; Theissen, 2012; Yang et al., 2012; Ahn et al., 2019; Fassas and

[1]See `https://www.coindesk.com/business/2022/10/07/morgan-stanley-says-crypto-etps-continue-to-grow-despite-bear-market/`. (Last accessed February 26, 2023.)

Siriopoulos, 2019), commodities (Kuiper et al., 2002; Peri et al., 2013; Dolatabadi et al., 2015; Hauptfleisch et al., 2016; Dimpfl et al., 2017), and foreign exchange (Chen and Gau, 2010).

Another branch of literature has investigated whether equity exchange-traded funds (ETFs) enhance price discovery in the underlying securities. The evidence presented is mixed. On the one hand, prior studies such as Lettau and Madhavan (2018), Madhavan (2016), and Madhavan and Sobczyk (2016) indicate that ETFs offer a supplementary layer of liquidity on top of the underlying securities, which can improve price discovery in the latter. This is because ETFs are a cost-effective tool for investors to make directional bets on the index, consequently reflecting new information before the underlying securities. This hypothesis is corroborated by several empirical studies (Richie et al., 2008; Marshall et al., 2013; Glosten et al., 2021). On the other hand, several studies have presented evidence showing that non-fundamental trades in the ETF may propagate to the underlying securities, causing mispricing and degrading informational efficiency (Broman, 2016; Israeli et al., 2017; Da and Shive, 2018; Brown et al., 2021).

In the cryptocurrency space, studies have largely focused on price discovery in Bitcoin markets. One branch of literature has investigated Bitcoin price dynamics within spot markets to determine which exchanges (Brandvold et al., 2015) and factors (Balcilar et al., 2017; Jang and Lee, 2017; Brauneis and Mestel, 2018; Beneki et al., 2019) explain price dynamics.

A second branch of literature has examined price discovery between Bitcoin spot and futures markets, making use of four popular cross-market metrics: Information Share (IS) (Hasbrouck, 1995), Component Share (CS) (Gonzalo and Granger, 1995), Information Leadership (IL) (Yan and Zivot, 2010), and the Information Leadership Share (ILS) (Putniņš, 2013). These studies have produced mixed results. On the one hand, Corbet et al. (2018)

apply the above-mentioned measures to one-minute CME, CBOE, and spot market data and find that price discovery is focused on the spot market. Similar evidence is found by Baur and Dimpfl (2019) using five-minute sampled data. On the other hand, Kapar and Olmo (2019) use daily-sampled data and find that the CME futures market dominates price discovery. Similarly, Fassas et al. (2020), Akyildirim et al. (2020), and Alexander et al. (2020) show that Bitcoin futures play a leading role in price discovery.

Our study contributes to the literature on price discovery in Bitcoin markets as – to the best of our knowledge – it is the first to empirically examine the price dynamics of Bitcoin ETPs in relation to spot markets. We apply four popular measures of price discovery to Bitcoin ETP and spot exchange data and show that spot markets dominate the price discovery process, suggesting that ETPs tend to lag in terms of informational efficiency.

The remainder of this paper is organised as follows. Section 2 presents the data. Section 3 describes the price discovery metrics. Section 4 discusses the results. Finally, Section 5 concludes our analysis.

2. Data

We use two data sources that span from August 2021 to July 2022. The first, CryptoCompare, provides spot transaction data on leading centralised exchanges. We obtain data on the BTC/USD and BTC/USDT[2] markets from the ten leading exchanges by volume: Binance, Bitfinex, Bitstamp, Coinbase, Gemini, Huobi, itBit, Kraken, Kucoin, and OKX. Descriptive statistics for the exchanges using daily sampled data are presented in Table 1.

[2]Some exchanges offer a BTC/USD market while others offer BTC/USDT. To account for potential movements in USDT/USD, we convert all BTC/USDT markets to BTC/USD using a market aggregate USDT/USD rate. The results for all analyses discussed in the paper remain the same, thus we do not report them due to spatial limitations.

Moreover, we present the illiquidity measure of Amihud (2002), which is calculated as

$$AI_i = \frac{1}{T}\sum_{t=1}^{T}\frac{|R_{i,t}|}{V_{i,t}} \tag{1}$$

where T is the number of days in the period of analysis, $|R_{i,t}|$ is the absolute daily return in percentage of asset i, and $V_{i,t}$ is the volume in millions of notional of the quote currency. The larger the value of AI, the greater the degree of illiquidity of the asset.

Exchanges are ranked by decreasing mean daily volume traded. Generally, the mean and standard deviation of returns are found to be the same across exchanges at -0.12% and 3.6%, respectively. In addition, the Bitcoin market on Binance is found to be the most liquid across exchanges according to the AI measure.

We use Bloomberg to obtain transaction data for the most popular Bitcoin ETPs issued by 21Shares, Coinshares, ETC Group, Iconic Funds, SEBA Bank AG, and VanEck. These ETPs trade on several stock exchanges located in the Eurozone. While price dynamics of an ETP issued by a particular issuer can differ across exchanges due to varying market activity on these exchanges, we focus on the exchanges with the most volume traded for each ETP. We present descriptive statistics for the ETPs using daily data in Table 2.

The majority of Bitcoin ETPs have a mean daily return of -0.09%, with the exception of SBTCU (-0.14%), and ABTC (0.06%) due to variations in launch date. The AI measure indicates that BTCE is the most liquid Bitcoin ETP. Nonetheless, the AI value for BTCE (0.0674) is around 56 times larger than that of Binance (0.0012), which suggests that even the most liquid Bitcoin ETP is around 56 times less liquid that the most liquid spot exchange. In unreported results, we estimate the AI for the SPDR equity ETF and individual stocks including TSLA, AMZN, MSFT, AAPL to be between 0.0001 and 0.00078. This similarly

Table 1: **Descriptive Statistics of Bitcoin Spot Exchanges.**

Exchange	**Base**	**Quote**	**Param**	**Mean**	**StDev**	**Min**	**Median**	**Max**
Binance	BTC	USDT	price	41,871	11,969	18,970	42,380	67,525
			return	-0.12	3.6	-15.38	-0.03	14.49
			volume	2,279,970,333	1,114,931,810	615,314,010	2,057,841,593	8,776,020,939
			AI	0.0012				
Coinbase	BTC	USD	price	41,880	11,984	18,948	42,415	67,554
			return	-0.12	3.6	-15.42	-0.01	14.52
			volume	673,327,112	337,238,581	163,733,089	617,922,091	2,087,246,485
			AI	0.0040				
Huobi	BTC	USDT	price	41,870	11,968	18,972	42,380	67,514
			return	-0.12	3.6	-15.41	-0.04	14.51
			volume	555,473,649	293,159,527	137,115,072	500,812,178	2,504,865,354
			AI	0.0049				
OKX	BTC	USDT	price	41,872	11,969	18,971	42,380	67,525
			return	-0.12	3.6	-15.4	-0.03	14.52
			volume	527,982,434	325,255,083	63,741,448	450,255,151	1,897,742,838
			AI	0.0060				
Kucoin	BTC	USDT	price	41,870	11,968	18,979	42,394	67,509
			return	-0.12	3.6	-15.4	-0.04	14.51
			volume	393,177,711	194,085,241	106,053,933	371,383,549	1,679,772,958
			AI	0.0070				
Bitfinex	BTC	USD	price	41,888	11,976	18,965	42,418	67,526
			return	-0.12	3.59	-15.53	-0.02	14.49
			volume	232,810,308	168,573,656	32,082,332	185,490,745	1,085,086,080
			AI	0.0131				
Kraken	BTC	USD	price	41,881	11,985	18,950	42,419	67,559
			return	-0.12	3.6	-15.47	-0.02	14.55
			volume	134,371,690	78,327,255	23,260,223	116,053,303	447,377,859
			AI	0.0204				
Bitstamp	BTC	USD	price	41,886	11,986	18,956	42,420	67,559
			return	-0.12	3.61	-15.55	-0.01	14.49
			volume	97,023,649	68,360,816	14,036,016	80,542,267	479,685,055
			AI	0.0309				
Gemini	BTC	USD	price	41,884	11,986	18,948	42,415	67,552
			return	-0.12	3.6	-15.4	-0.03	14.54
			volume	62,068,086	43,104,267	10,112,372	50,670,616	283,009,135
			AI	0.0474				
Bitfinex	BTC	USDT	price	41,872	11,969	18,979	42,377	67,517
			return	-0.12	3.6	-15.48	-0.01	14.61
			volume	50,601,341	38,119,450	2,124,543	40,282,227	223,731,253
			AI	0.0783				
Coinbase	BTC	USDT	price	41,872	11,970	18,977	42,379	67,530
			return	-0.12	3.59	-15.41	-0.03	14.59
			volume	27,309,774	15,056,375	2,316,301	24,842,512	111,971,110
			AI	0.1065				
itBit	BTC	USD	price	41,884	11,985	18,948	42,412	67,554
			return	-0.12	3.6	-15.49	-0.04	14.53
			volume	13,261,508	10,081,651	1,584,938	10,296,224	70,668,139
			AI	0.2455				
Kraken	BTC	USDT	price	41,874	11,971	19,001	42,379	67,512
			return	-0.12	3.6	-15.54	-0.08	14.52
			volume	12,958,329	8,882,283	1,440,347	10,785,588	62,099,533
			AI	0.2334				
Bitstamp	BTC	USDT	price	41,894	11,958	19,022	42,562	67,634
			return	-0.12	3.61	-16.11	0.0	14.39
			volume	750,717	1,096,083	1,936	446,162	11,475,061
			AI	8.6200				

This table presents descriptive statistics for daily Bitcoin prices, returns, and volumes over the period August 2021 to July 2022. We report the mean (**Mean**), standard deviation (**StDev**), minimum (**Min**), median (**Median**), and maximum (**Max**) values. Moreover, we report the Amihud illiquidity measure (AI) where the volume parameter in the denominator is in the millions of notional of the quote currency.

Table 2: **Descriptive Statistics of Bitcoin Exchange-Traded Products (ETPs).**

Issuer	**Ticker**	**Exchange**	**Quote**	**Param**	**Mean**	**StDev**	**Min**	**Median**	**Max**
ETC Group	BTCE	Xetra	EUR	price	36.33	9.55	17.52	36.65	57.76
				return	-0.09	3.43	-20.41	0	9.92
				volume	2,865,877	11,214,308	0	908,034	152,048,456
				market cap	785,922,300	345,048,300	310,831,400	720,241,400	1,667,034,000
				AI	0.0674				
VanEck	VBTC	Xetra	EUR	price	20.68	5.4	10.02	20.88	32.82
				return	-0.09	3.43	-20.04	0	10.21
				volume	1,856,566	5,062,089	0	423,666	44,544,488
				market cap	209,036,200	56,614,410	98,231,690	211,778,500	335,896,700
				AI	0.2354				
SEBA Bank AG	SBTCU	SIX	USD	price	4.16	1.2	1.85	4.24	6.75
				return	-0.14	3.53	-19.88	0	10.58
				volume	681,313	3,288,609	0	20,000	35,076,564
				market cap	73,278,340	15,955,170	41,906,200	73,732,000	110,194,000
				AI	36.5259				
21Shares	ABTC	SIX	USD	price	15.01	4.44	6.73	15.25	24.5
				return	0.06	7.08	-36.06	0	46.25
				volume	605,740	1,872,248	0	152,574	23,237,304
				market cap	314,024,400	97,922,430	156,472,000	303,231,000	577,426,000
				AI	1.9264				
Iconic Funds	XBTI	SIX	CHF	price	3.73	0.97	1.81	3.76	5.92
				return	-0.09	3.45	-20.51	0	10.14
				volume	245,743	1,235,972	0	30,594	21,164,432
				market cap	6,427,968	1,825,737	3,428,631	6,617,954	11,593,840
				AI	182.8244				
Coinshares	BITC	SIX	USD	price	41.71	12.01	18.56	42.6	68.07
				return	-0.09	4.58	-32.19	0	35.86
				volume	26,485	125,588	0	2,742	1,817,852
				market cap	336,187,200	92,189,760	173,105,000	323,565,000	569,732,000
				AI	62.1941				

This table presents descriptive statistics for daily Bitcoin ETP prices, returns, volumes, and market cap over the period August 2021 to July 2022. We report the mean (**Mean**), standard deviation (**StDev**), minimum (**Min**), median (**Median**), and maximum (**Max**) values. Moreover, we report the Amihud illiquidity measure (AI) where the volume parameter in the denominator is in the millions of notional of the quote currency.

highlights that the most liquid Bitcoin ETP is, on average, around 250 times less liquid than the largest tech stocks. To put things further into perspective, the aggregate market capitalization of the Bitcoin ETPs in our sample reached a maximum of around $3.2 billion, which is significantly lower than the market cap of large tech stocks, including TSLA and AAPL, which have consistently been valued as multi-trillion dollar companies during the period of analysis.

3. Methodology

There are two price discovery measures, which assume a common implicit efficient price that can be estimated using a vector error correction model (VECM). The Information Share (IS) (Hasbrouck, 1995), estimates the proportion of the efficient price innovation variance explained by innovations stemming from the different markets. Alternatively, the Component Share (CS) approach (Booth et al., 1999; Chu et al., 1999; Harris et al., 2002) adopts the permanent-transitory decomposition technique in Gonzalo and Granger (1995). Specifically, the permanent component represents the common efficient price, while the temporary component reflects deviations from the efficient price caused by trading fractions. Despite their disparate focus points, both measures adopt cointegration to constrain multiple price series to share a common efficient price.

Consider an asset that is trading on two venues, where $p_{i,t}$ denotes the log price of the asset on venue i at time t. We assume that the two price series are closely linked due to arbitrage and that they contain a random-walk element rendering them non-stationary. Following Hauptfleisch et al. (2016) and Corbet et al. (2018), we write the VECM representation for the two venues as

$$\Delta p_{1,t} = \alpha_1(p_{1,t-1} - p_{2,t-1}) + \sum_{i=1}^{200} \gamma_i \Delta p_{1,t-i} + \sum_{j=1}^{200} \delta_j \Delta p_{2,t-j} + \varepsilon_{1,t} \tag{2}$$

$$\Delta p_{2,t} = \alpha_2(p_{1,t-1} - p_{2,t-1}) + \sum_{k=1}^{200} \varphi_k \Delta p_{1,t-k} + \sum_{m=1}^{200} \phi_m \Delta p_{2,t-m} + \varepsilon_{2,t} \tag{3}$$

where $\Delta P_{i,t}$ represents the change in the log price series $p_{i,t}$ of venue i at time t.

We estimate CS from the normalised orthogonal coefficients to the vector of error correction as

$$CS_1 = \gamma_1 = \frac{\alpha_2}{\alpha_2 - \alpha_1} \qquad \text{and} \qquad CS_2 = \gamma_2 = \frac{\alpha_1}{\alpha_1 - \alpha_2}. \tag{4}$$

Using the covariance matrix of the reduced form VECM error terms, given as

$$M = \begin{pmatrix} m_{1,1} & 0 \\ m_{1,2} & m_{2,2} \end{pmatrix} = \begin{pmatrix} \sigma_1 & 0 \\ \rho\sigma_2 & \sigma_2(1-\rho^2)^{\frac{1}{2}} \end{pmatrix} \tag{5}$$

we compute IS as

$$IS_1 = \frac{(\gamma_1 m_{1,1} + \gamma_2 m_{1,2})^2}{(\gamma_1 m_{1,1} + \gamma_2 m_{1,2})^2 + (\gamma_2 m_{2,2})^2} \qquad \text{and} \qquad IS_2 = \frac{(\gamma_2 m_{2,2})^2}{(\gamma_1 m_{1,1} + \gamma_2 m_{1,2})^2 + (\gamma_2 m_{2,2})^2}. \tag{6}$$

The literature highlights that IS and CS are sensitive to the relative level of noise in each market. Hence, on their own, these measures are likely to overstate the contribution to price discovery of the less noisy market. Yan and Zivot (2010) and Putniņš (2013) show that a combination of the two measures can remove dependence on noise and liquidity shocks.

Specifically, the Information Leadership (IL) metric of Yan and Zivot (2010) is expressed as

$$IL_1 = \left| \frac{IS_1}{IS_2} \frac{CS_2}{CS_1} \right| \qquad \text{and} \qquad IL_2 = \left| \frac{IS_2}{IS_1} \frac{CS_1}{CS_2} \right|. \tag{7}$$

Unlike IS and CS, the IL measure does not represent a proportion, whereby the sum of IL_1 and IL_2 do not necessarily equal unity. Instead, IL_1 ranges from $[0, \infty)$, where values over (under) one imply that p_1 leads (lags) in the process of price discovery. To standardise IL, Putniņš (2013) proposes the Information Leadership Share (ILS), written as

$$ILS_1 = \frac{IL_1}{IL_1 + IL_2} \qquad \text{and} \qquad ILS_2 = \frac{IL_2}{IL_1 + IL_2}. \tag{8}$$

Values of ILS range between zero and one, with numbers higher (lower) than 0.5 suggesting that the corresponding market leads (lags) in price discovery.

4. Results

We calculate the above-mentioned metrics for all combinations of Bitcoin spot exchanges and ETPs using 1-minute, 5-minute, 60-minute, and 1 day sampling frequencies. The results we obtain for all exchange-ETP combinations are broadly consistent. Due to spatial limitations, Table 3 only shows the results for the top three exchanges and ETPs by average daily traded volume.

Table 3: **Price Discovery Metrics between Bitcoin Exchange-Traded Products (ETPs) and Spot Markets.**

Freq	**ETP**	**Exchange**	**Market**	**CS**	**IS**	**IL**	**ILS**
1 min	BTCE	$\text{Binance}_{\text{BTC/USDT}}$	ETP	0.065	0.004	0.06	0.004
			Exchange	0.935	0.996	16.762	0.996
		$\text{Coinbase}_{\text{BTC/USD}}$	ETP	0.069	0.005	0.066	0.004
			Exchange	0.931	0.995	15.148	0.996
		$\text{Huobi}_{\text{BTC/USDT}}$	ETP	0.065	0.004	0.062	0.004
			Exchange	0.935	0.996	16.045	0.996
	SBTCU	$\text{Binance}_{\text{BTC/USDT}}$	ETP	0.014	0.002	0.145	0.02
			Exchange	0.986	0.998	6.916	0.98
		$\text{Coinbase}_{\text{BTC/USD}}$	ETP	0.012	0.001	0.118	0.014
			Exchange	0.988	0.999	8.448	0.986
		$\text{Huobi}_{\text{BTC/USDT}}$	ETP	0.014	0.002	0.143	0.02
			Exchange	0.986	0.998	6.998	0.98
	VBTC	$\text{Binance}_{\text{BTC/USDT}}$	ETP	0.073	0.007	0.085	0.007
			Exchange	0.927	0.993	11.81	0.993
		$\text{Coinbase}_{\text{BTC/USD}}$	ETP	0.075	0.007	0.089	0.008
			Exchange	0.925	0.993	11.271	0.992
		$\text{Huobi}_{\text{BTC/USDT}}$	ETP	0.072	0.007	0.086	0.007
			Exchange	0.928	0.993	11.564	0.993
5 min	BTCE	$\text{Binance}_{\text{BTC/USDT}}$	ETP	0.065	0.016	0.232	0.051
			Exchange	0.935	0.984	4.311	0.949
		$\text{Coinbase}_{\text{BTC/USD}}$	ETP	0.071	0.015	0.203	0.04
			Exchange	0.929	0.985	4.925	0.96
		$\text{Huobi}_{\text{BTC/USDT}}$	ETP	0.064	0.016	0.233	0.051
			Exchange	0.936	0.984	4.294	0.949
	SBTCU	$\text{Binance}_{\text{BTC/USDT}}$	ETP	0.017	0.003	0.19	0.035
			Exchange	0.983	0.997	5.265	0.965
		$\text{Coinbase}_{\text{BTC/USD}}$	ETP	0.01	0.001	0.131	0.017
			Exchange	0.99	0.999	7.64	0.983
		$\text{Huobi}_{\text{BTC/USDT}}$	ETP	0.017	0.003	0.191	0.035
			Exchange	0.983	0.997	5.226	0.965
	VBTC	$\text{Binance}_{\text{BTC/USDT}}$	ETP	0.072	0.009	0.123	0.015
			Exchange	0.928	0.991	8.151	0.985
		$\text{Coinbase}_{\text{BTC/USD}}$	ETP	0.086	0.009	0.098	0.009
			Exchange	0.914	0.991	10.23	0.991
		$\text{Huobi}_{\text{BTC/USDT}}$	ETP	0.071	0.009	0.124	0.015
			Exchange	0.929	0.991	8.08	0.985
60 min	BTCE	$\text{Binance}_{\text{BTC/USDT}}$	ETP	0.13	0.032	0.221	0.046
			Exchange	0.87	0.968	4.533	0.954
		$\text{Coinbase}_{\text{BTC/USD}}$	ETP	0.138	0.033	0.213	0.043
			Exchange	0.862	0.967	4.7	0.957
		$\text{Huobi}_{\text{BTC/USDT}}$	ETP	0.129	0.032	0.221	0.046
			Exchange	0.871	0.968	4.533	0.954

Continued on next page

Freq	ETP	Exchange	Market	CS	IS	IL	ILS
	SBTCU	$\text{Binance}_{\text{BTC/USDT}}$	ETP	0.024	0.005	0.201	0.039
			Exchange	0.976	0.995	4.978	0.961
		$\text{Coinbase}_{\text{BTC/USD}}$	ETP	0.021	0.005	0.216	0.044
			Exchange	0.979	0.995	4.64	0.956
		$\text{Huobi}_{\text{BTC/USDT}}$	ETP	0.024	0.005	0.201	0.039
			Exchange	0.976	0.995	4.973	0.961
	VBTC	$\text{Binance}_{\text{BTC/USDT}}$	ETP	0.139	0.029	0.185	0.033
			Exchange	0.861	0.971	5.405	0.967
		$\text{Coinbase}_{\text{BTC/USD}}$	ETP	0.147	0.03	0.183	0.032
			Exchange	0.853	0.97	5.478	0.968
		$\text{Huobi}_{\text{BTC/USDT}}$	ETP	0.138	0.029	0.186	0.034
			Exchange	0.862	0.971	5.368	0.966
1 day	BTCE	$\text{Binance}_{\text{BTC/USDT}}$	ETP	0.369	0.142	0.283	0.074
			Exchange	0.631	0.858	3.53	0.926
		$\text{Coinbase}_{\text{BTC/USD}}$	ETP	0.372	0.143	0.282	0.073
			Exchange	0.628	0.857	3.552	0.927
		$\text{Huobi}_{\text{BTC/USDT}}$	ETP	0.368	0.142	0.283	0.074
			Exchange	0.632	0.858	3.529	0.926
	SBTCU	$\text{Binance}_{\text{BTC/USDT}}$	ETP	0.046	0.213	5.659	0.97
			Exchange	0.954	0.787	0.177	0.03
		$\text{Coinbase}_{\text{BTC/USD}}$	ETP	0.046	0.212	5.631	0.969
			Exchange	0.954	0.788	0.178	0.031
		$\text{Huobi}_{\text{BTC/USDT}}$	ETP	0.047	0.213	5.544	0.968
			Exchange	0.953	0.787	0.18	0.032
	VBTC	$\text{Binance}_{\text{BTC/USDT}}$	ETP	0.371	0.141	0.279	0.072
			Exchange	0.629	0.859	3.58	0.928
		$\text{Coinbase}_{\text{BTC/USD}}$	ETP	0.373	0.142	0.278	0.072
			Exchange	0.627	0.858	3.598	0.928
		$\text{Huobi}_{\text{BTC/USDT}}$	ETP	0.37	0.141	0.279	0.072
			Exchange	0.63	0.859	3.579	0.928

This table presents the values for the Component Share (**CS**), Information Share (**IS**), Information Leadership (**IL**), and Information Leadership Share (**ILS**) between Bitcoin ETP and spot markets based on 1-minute, 5-minute, 60-minute, and 1-day sampled price data.

For all sampling frequencies and metrics considered, the spot market across all exchanges leads in price discovery[3]. The ILS across spot exchanges is above 90%, implying that most information impacting Bitcoin prices stems from spot markets. This may be due to (i) the greater degree of liquidity on spot exchanges as

[3]The sole exception is the SBTCU ETP sampled at daily intervals, a potential anomaly given that higher data frequencies for this ETP suggest that spot markets lead.

indicated by the AI measure, (ii) more established continuously traded spot markets on crypto exchanges compared to limited market-hours trading on equity exchanges, (iii) greater degree of anonymity on crypto exchanges, which may attract informed investors, and (iv) the fact that ETP creations is preceded by a hedge transaction in spot markets. Additionally, ILS is larger for higher frequency data, which supports the notion that information is more quickly reflected in spot markets due to their dynamic and liquid nature — as indicated by the smaller AI values for crypto spot exchanges relative to ETPs.

5. Conclusion

This study investigates price discovery between Bitcoin ETPs and spot markets using four popular metrics, and shows that spot markets dominate this process due to their deeper liquidity, continuous trading hours, and greater degree of anonymity. Nonetheless, ETPs may play a more significant role in the future as this market matures and complies with regulatory frameworks, thus gaining popularity among institutional investors.

Our findings underscore the importance of trading activities on centralised crypto exchanges in determining crypto prices despite regulators broadly dismissing these markets in favour of more traditional regulated venues.

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